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Research article

Critical sectors and paths for climate change mitigation within supply chain networks

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ABSTRACT

Certain sectors and paths along supply chains play a critical role in climate change mitigation. We develope a consumption-based framework, which combines input–output analysis, a power-of-pull approach and structural path analysis, and applied it to supply chain networks derived from 2010 and 2012 Jing-Jin-Ji interregional input–output tables. The aim of this study is to identify (1) the key economic sectors for controlling carbon emissions and their changes, (2) the critical directions from a carbon-pulling sector to the emissions of key economic sectors, and (3) the paths with the largest carbon emissions flux in these critical directions. Our results show that the key sectors are from Hebei and Tianjin, more concentrated in Hebei. Most sectors have the largest pulling power over their own carbon emissions, and within-region connections dominated in the emission network, with a stronger tie between Beijing and the other two regions. Critical paths along carbon-pulling directions are located in tiers 0 and 1. Our framework can provide new insight into the creation of carbon emissions control policies.

1. Introduction

With the implementation of the 13th 5-year plan, promoting energy efficiency and reducing carbon intensity have become binding priorities of the Chinese government. The task of national reduction in carbon emissions is generally allocated to provinces or industries. Currently, these allocations are based on direct geographic or sectoral carbon emissions, using production-based accounting methods (Liang et al., 2017). These methods neglect indirect emissions embodied in the supply chain with informative linkages (Liang et al., 2016), and may create unequal policy pressure on industries in provinces at different stages of development (Du et al., 2017). Considering that the major drivers of carbon emissions include local, domestic, and foreign consumptions, the allocation of the burden of mitigation requires further exploration (Davis and Caldeira, 2010).

Consumption-based accounting methods consider emissions embodied in international or interregional trade (Guo et al., 2012; Mi et al., 2016; Zhang et al., 2015). Since input–output models (IOMs) can capture emissions embodied in trade, an increasing number of studies have focused on consumption-based carbon emissions (Feng et al., 2015; Jakob and Marschinski, 2012). In particular, many studies have focused on China's embodied carbon emissions in trade (Feng et al., 2013; Meng et al., 2013; Mi et al., 2016; Xu et al., 2011; Xu et al., 2017). Using IOMs, it is possible to quantify the transfer of emissions from one region to another. Further, each sector produces goods and services for final consumption and intermediate use in other sectors (Chen et al., 2017b); i.e., sectors are the agents of cross-reginal emission transfer. Therefore, some sectors may play significant roles in contributing, controlling, or brokering emissions for the entire system (Chen and Chen, 2016; Wang et al., 2017a; Wen et al., 2014). Critical sectors were initially identified for their economic importance. For example, Chenery and Watanabe (1958), Rasmussen (1956), and Dietzenbacher (1992) have proposed a series of IOM-based methods for identification of critical economic sectors. More recently, critical sector identification has been applied increasingly to resource or environmental extended input–output tables, in pace with the rapid development of social/ecological network analysis. Alcántara and Padilla (2003) designed a method based on input–output tables and the elasticity of final energy consumption demands to identify which sectors should be controlled in Spain. Chen et al. (2017a) used linkage analysis to pinpoint the critical sectors for urban decarbonization. Chen and his colleges proposed a network control method to assess the level of influence of a sector within a system and applied this method to different subjects, including energy consumption, carbon emissions, and the energy–water nexus (Chen and

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Chen, 2015, 2016; Lu et al., 2015; Wang and Chen, 2016). Wang et al. (2017b) applied several social network analytical methods to interregional carbon flows embodied in domestic trade and identified the roles of critical sectors. Power-of-pull (PoP) approach is a convenient method used for the identification of critical sectors in a systemic view (Wang et al., 2017a), which gives a rank of the most powerful sectors as key nodes that pull others. In addition to node identification in the system, the linkage feature, which identifies flow among sectors, has become a popular research tool in the past few decades. Structural path analysis (SPA) is a method based on IOM that has typically been applied to quantify environmental transmissions and identify important paths along supply chains. Over the past decades, several studies have used SPA (Defourny and Thorbecke, 1984; Khan and Thorbecke, 1989; Lenzen, 2003, 2002; Sonis and Hewings, 1998) to analyze flows of energy (Hong et al., 2016; Zhang et al., 2017), carbon (Acquaye et al., 2011; Liang et al., 2016b; Yang et al., 2015), water (Llop and Ponce-Alifonso, 2015), and other resources (Seung, 2016) or pollutants (Meng et al., 2015; Nagashima et al., 2016) through input–output relationships. The identification of critical sectors and paths has successfully assisted the creation and implementation of policies. Nodes and linkages are two closely connected aspects of this method. For example, a highly ranked sector may play a significant role in the emission transferring process. Critical sectors and paths together affect the environmental performance of the economic system (Hanaka et al., 2017; Liang et al., 2016). However, previous studies have tended to focus on only one of these aspects or on both aspects separately; the influence of a path on the entire system has rarely been addressed. In general, a path with a high amount of embodied emissions is not a critical path *per se* controlling the performance of the entire system. Additionally, the question of which paths would affect the system performance of critical sectors has not been sufficiently discussed in previous studies.

In this study, we propose a framework based on IOM, the PoP approach, and SPA to identify critical sectors of interregional carbon emissions transfer and to indirectly identify the important carbon transfer paths across the Jing-Jin-Ji (Beijing-Tianjin-Hebei) region in China. Viewed from the demand side, we focused on the key sectors and their critical paths through supply chain among the regions. This study was the first application of our proposed framework at an interregional scale, and we expect this framework to provide new and promising insights into the creation and implementation of policies. This paper is organized as follows: Section 2 provides a detailed introduction to the methods and data, Section 3 elaborates the results of the Jing-Jin-Ji area case study, Section 4 provides a discussion of the results, and finally, we draw brief conclusions in Section 5.

2. Methodology and data

2.1. Methodology

The first step of our framework was to apply PoP to the emission technical coefficient matrix of the Jing-Jin-Ji area to identify the key sectors of the system. IOM was then used to extract the induced carbon transfer networks. PoP was applied to the networks again to determine the relative importance of pulling sector i to the carbon emissions performance of sector j, yielding a pulling direction $i \rightarrow j$. Along this direction, the critical paths from i to j were identified by SPA. This procedure allowed us to identify the important paths for the key sectors. To avoid confusion, we define several concepts in Table 1.

Table 1
Definitions of the terms frequently used in this paper. PoP: power-of-pull approach; SPA: structural path analysis.

Keywords	Meaning
Key sector	A sector identified by PoP for the whole system
Pulling sector	A sector identified by PoP for a targeted sector
Direction	The effect from pulling sector i to key sector j, as identified by PoP
Path	Structural path derived from SPA

2.1.1. Input–output model

In a three-region interregional input–output table, sectors have the following relationships:

$$x = Ax + y = (I - A)^{-1}y = Ly \tag{1}$$

$$A = \begin{bmatrix} A^{rr} & A^{rs} & A^{rt} \\ A^{sr} & A^{ss} & A^{st} \\ A^{tr} & A^{ts} & A^{tt} \end{bmatrix} \tag{2}$$

where x is the total output vector (of, say, $3n$ sectors for 3 regions each with n sectors), A is the technical coefficient matrix ($3n \times 3n$) for the entire system, and r, s, and t represent the three different regions, each with n sectors. A^{rr} and A^{rs}, for example, describe the purchases for unit production within region r and from regions r to s, respectively. The total final-use (of three regions) vector is y $(3n \times 1)$, and I is the identity matrix of A. The matrix $L = (I - A)^{-1}$ is known as the Leontief inverse, reflecting the total requirement of the sectors.

Based on Eq. (1), the induced final-use output can be allocated to each sector as

$$X = (I - A)^{-1}\hat{y} \tag{3}$$

where X is the total output matrix, the ith column of which X denotes the output derived from the final use of the ith sector; the accent "^" on a vector denotes the diagonal form of the vector. For transforming the input-output relationships into a carbon-emission network, we assume that the derived outputs are all distributed for intermediate use, the final-use induced carbon flows form a network as follows:

$$G_i = \hat{c}A\hat{X}_{,i}, \tag{4}$$

where G_i is the final use of the i^{th} sector induced network, and $\hat{c}$ is the diagonal matrix form of the direct carbon coefficient vector c $(3n \times 1)$. Based on this network, the embedded carbon linkages between sectors can be extracted with PoP and SPA methods.

2.1.2. Power-of-pull approach

PoP, first proposed by Dietzenbacher (1992), is an eigenvector-based method that is similar to eigenvector centrality in social network analysis (Luo, 2013b). PoP often uses a technical coefficient matrix or weighted relationship matrix as input, whereas a binary-adjacent matrix is used in eigenvector centrality. According to PoP, the power of a sector is determined by the powers of the sectors to which it is connected. In turn, the power indexes of these sectors are determined by their connected sectors. Therefore, PoP is an infinite regress problem and can be written as Eq. (5):

$$\lambda p' = p'M, \tag{5}$$

where M is the weighted relationship matrix, in this study the network of emission transfer through sectors ($3n \times 3n$), p' $(1 \times 3n)$ is the transpose of the vector of power indexes for the X matrix, and λ is the dominant eigenvalue, also as a scalar constant. The solution for p' is the left-hand Perron eigenvector for key sector identification in the consumption-based input–output relationships. The normalized power indexes are calculated as follows:

$$z' = mp'/(p'e), \tag{6}$$

where m is the number of sectors, e is the column summation vector where all $e_i = 1$, and is the vector of standardized power indexes with an average of 1, denoting how powerfully the activities of specific sectors can pull the activity of the overall system. Without loss of generality, sectors with an above-average pulling power ($z_i > 1$) are

designated as critical.

2.1.3. Structural path analysis

Eq. (4) can be further expanded based on a Taylor series approximation, which is the theoretical foundation of SPA. Eqs. (7) and (8) show how the critical paths are extracted from the input–output relationships:

$$tc = \hat{c}(I - A)^{-1}y = \overbrace{\hat{c}Iy}^{tier0} + \overbrace{\hat{c}Ay}^{tier1} + \overbrace{\hat{c}A^2y}^{tier2} + \overbrace{\hat{c}A^3y}^{tier3} + \overbrace{\hat{c}A^4y}^{tier4} + \cdots \tag{7}$$

Here, tc is the consumption-based total carbon emissions vector. Essentially, the carbon emissions embodied in goods and services transfer infinitely among sectors through trade. In Eq. (7), $\hat{c}Iy$ represents the direct carbon emissions emitted for a given demand y, and $\hat{c}A^n y$ represents the indirect carbon emissions for a given final demand y at the nth production tier. Thus, we can track the carbon emissions input from sector i to sector j as

$$\overbrace{c_i A_{ij} y_j}^{tier1} + \overbrace{c_i A_{ik} A_{kj} y_j}^{tier2} + \cdots, \forall\, k \tag{8}$$

For example, the value of $c_i A_{ik} A_{kj} y_j$ represents the amount of carbon emissions input from sector i in tier 2 to sector j. In this paper, we use $i \rightarrow k \rightarrow j$ to denote the carbon transfer path of $c_i A_{ik} A_{kj} y_j$. The same pattern is held among all tiers. SPA is *de facto* an infinite and time consuming method for critical path identification. Previous studies have shown that the top paths ranked by flux were mainly within the range of tier 0–4 4 (Lenzen et al., 2013; Liang et al., 2015). Therefore, in this study we calculated only the paths spanning from tier 0 to tier 4.

2.2. Data

We employed the latest available provincial multi-regional input–output table compiled by the Chinese Academy of Science (Liu et al., 2015a). To focus on the Jing-Jin-Ji region, we extracted data for the three provinces and combined the remainder of the data. Carbon emissions data were collected from China Emission Accounts & Datasets (www.ceads.net) (Liu et al., 2015b. We followed the method of Liang et al. (2016a) to match the sector classifications of the two datasets. This table was based on the 2010 and 2012 economy, and provides interaction data for three provinces and 27 sectors in China (Appendix A). The table is non-competitive, where import has been omitted from interregional trade.

3. Results

3.1. Key sectors for the system

Key sectors for the system were identified by applying PoP to the emission technical coefficient matrix $\hat{c}A$, which includes endogenous inter-sector linkages and unit carbon emissions. The results indicate the relative importance of a sector for emission control within the system, taking into consideration the performance of a production unit. Fig. 1 shows the power index for each sector in the Jing-Jin-Ji region in 2010(a) and 2012(b). The dotted lines indicate the mean of the power indexes, which is equal to 1. From Fig. 1a, it is clear that all sectors in Beijing had small power indexes, less than the mean, while most sectors in Hebei had above-average power indexes. Sectors in Tianjin were scattered moderately around the mean. The average power indexes were 0.155, 0.884, and 1.961 for Beijing, Tianjin, and Hebei, respectively. These results indicate that Hebei is the key province for control of carbon emissions for the entire system. From a sectoral perspective, PSE (id = 22), MTP (15), and NMP (13) were the sectors with the largest power indexes among the three regions. For example, PSE (22) was ranked first in Tianjin and Hebei and third in Beijing according to power index, and MTP (15) was ranked second in Hebei, fifth in Tianjin, and second in Beijing. PSG (23) was the most powerful sector in Beijing, pulling carbon emissions from the entire system, but had only moderate rankings in the other two regions. In total, 32 out of 81 sectors had power indexes above the average level. While in 2012, the sectors with high (> 1) power indexes are all from Hebei, in which PSE (22) in Hebei reaches a higher value, farther from the average level. However, the pulling powers of sectors of Beijing and Tianjin turn to be lower than average. We infer that sectors with a higher power index are more critical for the performance of the system.

3.2. Pulling sectors for key sectors

All pulling sectors for the key sectors were identified by applying PoP to the final-use induced carbon transfer network G_i. The results indicate how important a pulling sector was in the supply chain of a key sector, in terms of pulling both direct and indirect emissions of the key sector. Fig. 2 provides two subplots visualizing the relationship between the pulling sectors and key sectors by emphasizing pulling sectors that had high and low power indexes of year 2010 (Fig. 2a) and 2012 (Fig. 2b). PoP was used to rank the critical pulling sectors and directions. For example, in 2010, the largest direction for key sector SPM (14) in Beijing (hereafter, SPM_{bj} (14), where the subscripts $_{bj}$, $_{tj}$, and $_{hb}$ represent Beijing, Tianjin, and Hebei, respectively) was PSE_{bj} (22) → SPM_{bj} (14), with a pulling power of 29.712, followed by MMD_{bj} (4) → SPM_{bj} (14) and SPM_{bj} (14) → SPM_{bj} (14), with pulling powers of 26.443 and 19.426, respectively. These directions were ranked as the top three critical paths for pulling SPM_{bj} (14) carbon emissions. Consequently, PSE_{bj} (22), MMD_{bj} (4), and SPMbj (14) were the most important pulling sectors for SPM_{bj} (14). In general, a critical pulling sector for a key sector had a critical direction from itself to the key sector.

Each sector played an important role in pulling its own carbon emissions (Fig. 2a and b). In 2010, from a regional perspective, Hebei sectors had the greatest power to pull their own carbon emissions, with an average power index of 55.305, followed by Tianjin (53.327) and Beijing (41.271). These results indicate that the carbon emissions of sectors in Hebei were driven more powerfully by the sectors or emission origin. From a sectoral perspective, all sectors had high power to pull their own carbon emissions, as highlighted in Fig. 2a (reddest diagonal). Therefore, to control the carbon emissions of most sectors, examination on the sectors themselves should be a priority. Only three sectors (NMP_{bj} (13), PSE_{bj} (22), and NMP_{tj} (13)) had one above-average pulling sector: themselves. Other sectors had 2 to 12 above-average pulling sectors. However, the pulling effects from other sectors to the key sectors were much smaller than those from themselves. The average of non-diagonal pulling relationships (Fig. 2a) within Beijing, Tianjin, and Hebei were 1.508, 1.062, and 0.9861, respectively, indicating relatively tight cross-sector relationships within Beijing. A large number of sectors had above-average pulling power on multiple key sectors within their own regions. PSE_{bj} (22) was the most influential sector in Beijing, with above-average pulling power on all other sectors in Beijing except OMI_{bj} (21), PPC_{bj} (11), NMP_{bj} (13), and TSP_{bj} (25). This was also the most influential sector of the entire system in terms of the number of sectors pulled. PSE_{tj} (22), SPM_{tj} (14), and SPM_{hb} (14) were the next top-ranking sectors, with broad pulling effects on other sectors in their regions. In contrast, cross-regional pulling effects among sectors were much smaller. Only SPM_{hb} (14) had an above-average pulling power of 11.628 on OMI_{bj} (21). Fig. 2a further demonstrates the within-region and cross-regional relationships in greater detail. The directions between Tianjin and Hebei were clearly stronger than their directions with Beijing, although nearly all directions were below average. In particular, MMD_{tj} (4) had the weakest pulling power (approximately 0) to sectors in other regions, and sectors in Tianjin and Hebei had little pulling power to PSE_{bj} (22). In general, within-region pulling directions were much stronger than cross-regional directions. The average pulling power of cross-regional directions was 0.004, compared with 2.992 for within-region directions.

In 2012, though the reddest points remained at the diagonal

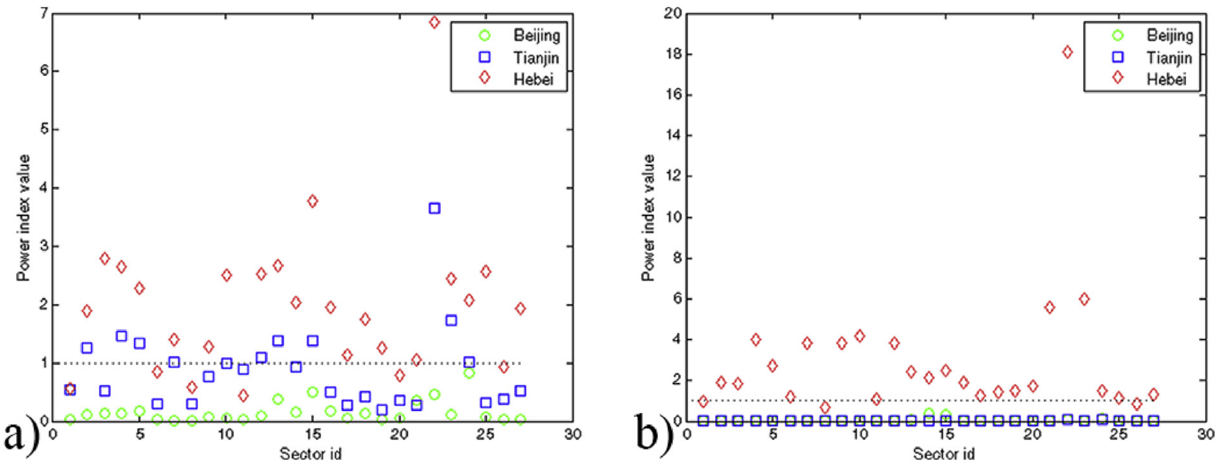

Fig. 1. Power index for each sector in the Jing-Jin-Ji region, a) for 2010, b) for 2012.

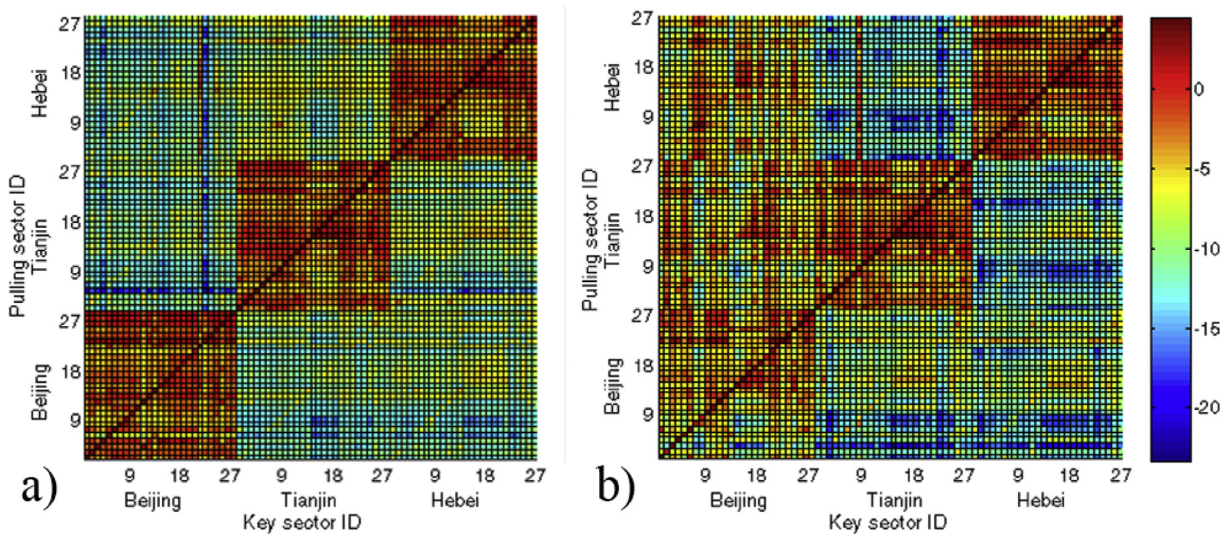

Fig. 2. Relationships between pulling sectors and key sectors. a) Map of logarithm of power indexes in 2010; b) map of logarithm of power indexes in 2012.

(Fig. 2b), which implied that self-pulling power of sectors were still predominant, and relationships within each region were with major importance. That might attribute to the convenient access of transportation and policy support within a region, and the region integration remained ongoing at an earlier chapter. However, there was an obvious change in the emission transferring network compared to that of 2010. Above all, the self-pulling power of Beijing weakened as that of Tianjin and Hebei strengthened to a comparable scale. With the closer linkages between Beijing and the two regions, Beijing became more dependent on the "import" of agricultural and industrial products from Tianjin and Hebei, while the latter two regions relied more on services that Beijing provided. It is then comprehensible that with a more interdependent economic relationship, Tianjin and Hebei's sectoral emissions were more largely pulled by sectors in Beijing, as the lower parts in Fig. 2b were redder than in Fig. 2a. While the cross-regional relationships were mainly colder between Tianjin and Hebei (implying the smaller pulling interaction between the two regions), except for the FLF_{tj} sector was pulled by sectors in Hebei, showing a higher reliance between them in the certain sector. To sum up, as time passed, Beijing strengthened network ties with the other two regions, influencing the others' emission performance with a growing power through more interactive paths. Thus, the cooperation among the three also needs attention for a better control.

3.3. Critical paths from pulling sectors to key sectors

The ranking of the directions allowed us to determine the relative importance of the key sectors. However, a direction is a comprehensive evaluation of the effect of one sector on another, which encompasses infinite mutual reinforcement among all sectors. To assist in policy creation, further decomposition of these directions is essential. Along a direction, SPA was used in this study to identify the most important pathway from the pulling sectors to the key sectors.

We selected the top five key sectors as examples to illustrate the above-average directions for the key sectors and the largest paths along these directions (Table 2). In 2010, the most important paths along these directions were located mainly in tiers 0 and 1. In particular, tier 0 paths contributed more than 85% of the carbon emissions of corresponding directions, which were ranked first among the key sectors. These paths confirmed the results of the PoP analysis that a sector should be the major contributor to carbon emissions performance within that sector. The flow of a path did not always agree with the power index. For example, the flow of the tier 0 path MTP_{hb} was smaller than that of the tier 1 path $SPM_{hb} \rightarrow MTP_{hb}$. In contrast, the power indexes of the corresponding directions were 64.708 and 13.343, respectively. The power index was used to evaluate the importance of a direction to the key sector, and SPA was performed to further quantify the critical path to that direction. The ranking of the direction was not

Table 2
Directions and paths for selected key sectors.

	Key sector	R[a]	Direction	Power index	Largest Path	Tier	Flow[b]	Share A[c]	Share B[d]
2010	PSE_{hb}	1	$PSE_{hb} \rightarrow PSE_{hb}$	69.146	PSE_{hb}	0	50.386	5.98%	85.97%
			$CMD_{hb} \rightarrow PSE_{hb}$	3.543	$CMD_{hb} \rightarrow PSE_{hb}$	1	2.710	0.32%	82.31%
			$OTR_{hb} \rightarrow PSE_{hb}$	2.961	$OTR_{hb} \rightarrow PSE_{hb}$	1	0.078	0.01%	60.08%
			$TSP_{hb} \rightarrow PSE_{hb}$	1.892	$TSP_{hb} \rightarrow PSE_{hb}$	1	0.099	0.01%	54.61%
	MTP_{hb}	2	$MTP_{hb} \rightarrow MTP_{hb}$	64.708	MTP_{hb}	0	0.299	0.04%	87.09%
			$SPM_{hb} \rightarrow MTP_{hb}$	13.343	$SPM_{hb} \rightarrow MTP_{hb}$	1	4.722	0.56%	69.56%
	PSE_{tj}	3	$PSE_{tj} \rightarrow PSE_{tj}$	72.334	PSE_{tj}	0	8.037	0.95%	84.16%
			$CMD_{hb} \rightarrow PSE_{tj}$	3.084	$CMD_{hb} \rightarrow PSE_{tj}$	1	0.000	0.00%	72.69%
			$OTR_{hb} \rightarrow PSE_{tj}$	2.298	$OTR_{hb} \rightarrow PSE_{tj}$	1	0.0101	0.00%	66.33%
	PNG_{hb}	4	$PNG_{hb} \rightarrow PNG_{hb}$	55.909	PNG_{hb}	0	0.170	0.02%	99.47%
			$SPM_{hb} \rightarrow PNG_{hb}$	9.678	$SPM_{hb} \rightarrow PNG_{hb}$	1	0.197	0.02%	72.74%
			$PSE_{hb} \rightarrow PNG_{hb}$	4.218	$PSE_{hb} \rightarrow PNG_{hb}$	1	0.287	0.03%	65.65%
			$OTR_{hb} \rightarrow PNG_{hb}$	1.7	$OTR_{hb} \rightarrow PNG_{hb}$	1	0.007	0.00%	72.01%
			$OMS_{hb} \rightarrow PNG_{hb}$	1.395	$OMS_{hb} \rightarrow PNG_{hb}$	1	0.001	0.00%	59.06%
			$MTP_{hb} \rightarrow PNG_{hb}$	1.194	$MTP_{hb} \rightarrow PNG_{hb}$	1	0.000	0.00%	28.62%
			$MMD_{hb} \rightarrow PNG_{hb}$	1.005	$MMD_{hb} \rightarrow SPM_{hb} \rightarrow PNG_{hb}$	2	0.001	0.00%	62.84%
	NMP_{hb}	5	$NMP_{hb} \rightarrow NMP_{hb}$	75.798	NMP_{hb}	0	14.952	1.78%	88.80%
			$NMM_{hb} \rightarrow NMP_{hb}$	3.428	$NMM_{hb} \rightarrow NMP_{hb}$	1	0.010	0.00%	84.21%
2012	PSE_{hb}	1	$PSE_{hb} \rightarrow PSE_{hb}$	76.046	PSE_{hb}	0	19.881	2.05%	74.24%
			$CMD_{hb} \rightarrow PSE_{hb}$	1.487	$CMD_{hb} \rightarrow PSE_{hb}$	1	0.629	0.06%	60.45%
	GWP_{hb}	2	$GWP_{hb} \rightarrow GWP_{hb}$	49.253	GWP_{hb}	0	0.014	0.00%	93.07%
			$PSE_{hb} \rightarrow GWP_{hb}$	18.907	$PSE_{hb} \rightarrow GWP_{hb}$	1	0.237	0.02%	57.05%
			$CPP_{hb} \rightarrow GWP_{hb}$	2.329	$CPP_{hb} \rightarrow GWP_{hb}$	1	0.001	0.00%	44.16%
			$SPM_{hb} \rightarrow GWP_{hb}$	2.009	$SPM_{hb} \rightarrow GWP_{hb}$	1	0.026	0.00%	28.61%
			$CMD_{hb} \rightarrow GWP_{hb}$	1.983	$CMD_{hb} \rightarrow GWP_{hb}$	1	0.043	0.00%	54.97%
			$MMD_{hb} \rightarrow GWP_{hb}$	1.099	$MMD_{hb} \rightarrow SPM_{hb} \rightarrow GWP_{hb}$	2	0.000	0.00%	19.87%
			$MTP_{hb} \rightarrow GWP_{hb}$	1.052	$MTP_{hb} \rightarrow GWP_{hb}$	1	0.000	0.00%	48.50%
	OMI_{hb}	3	$OMI_{hb} \rightarrow OMI_{hb}$	47.692	OMI_{hb}	0	0.014	0.00%	85.55%
			$PSE_{hb} \rightarrow OMI_{hb}$	17.456	$PSE_{hb} \rightarrow OMI_{hb}$	1	0.450	0.05%	50.84%
			$SPM_{hb} \rightarrow OMI_{hb}$	4.930	$SPM_{hb} \rightarrow OMI_{hb}$	1	0.175	0.02%	45.80%
			$CPP_{hb} \rightarrow OMI_{hb}$	3.123	$CPP_{hb} \rightarrow OMI_{hb}$	1	0.004	0.00%	46.99%
			$MMD_{hb} \rightarrow OMI_{hb}$	2.019	$MMD_{hb} \rightarrow SPM_{hb} \rightarrow OMI_{hb}$	2	0.001	0.00%	32.08%
			$MTP_{hb} \rightarrow OMI_{hb}$	1.575	$MTP_{hb} \rightarrow OMI_{hb}$	1	0.001	0.00%	49.12%
	PPR_{hb}	4	$PPR_{hb} \rightarrow PPR_{hb}$	46.208	PPR_{hb}	0	0.156	0.02%	80.69%
			$PSE_{hb} \rightarrow PPR_{hb}$	18.284	$PSE_{hb} \rightarrow PPR_{hb}$	1	0.704	0.07%	44.76%
			$OMI_{hb} \rightarrow PPR_{hb}$	4.059	$OMI_{hb} \rightarrow PPR_{hb}$	1	0.002	0.00%	65.27%
			$CPP_{hb} \rightarrow PPR_{hb}$	2.955	$CPP_{hb} \rightarrow PPR_{hb}$	1	0.005	0.00%	38.66%
			$TPB_{hb} \rightarrow PPR_{hb}$	2.234	$TPB_{hb} \rightarrow PPR_{hb}$	1	0.005	0.00%	62.13%
			$SPM_{hb} \rightarrow PPR_{hb}$	1.465	$SPM_{hb} \rightarrow MTP_{hb} \rightarrow PPR_{hb}$	2	0.050	0.01%	18.30%
			$MTP_{hb} \rightarrow PPR_{hb}$	1.292	$MTP_{hb} \rightarrow PPR_{hb}$	1	0.002	0.00%	53.46%
	MMD_{hb}	5	$MMD_{hb} \rightarrow MMD_{hb}$	51.136	MMD_{hb}	0	0.236	0.02%	70.38%
			$PSE_{hb} \rightarrow MMD_{hb}$	18.534	$PSE_{hb} \rightarrow MMD_{hb}$	1	2.583	0.27%	43.68%
			$CPP_{hb} \rightarrow MMD_{hb}$	4.542	$CPP_{hb} \rightarrow MMD_{hb}$	1	0.030	0.00%	42.40%
			$CMD_{hb} \rightarrow MMD_{hb}$	1.092	$CMD_{hb} \rightarrow PPC_{hb} \rightarrow MMD_{hb}$	2	0.177	0.02%	26.92%
			$PPC_{hb} \rightarrow MMD_{hb}$	1.060	$PPC_{hb} \rightarrow MMD_{hb}$	1	0.210	0.02%	60.51%

[a] R: ranking of the key sectors.
[b] Flow: carbon flow along the path, $MtCO_2$.
[c] Share A: the share of the flow to the total carbon emissions of the system.
[d] Share B: the share of the flow to the total carbon emissions along the direction.

applicable to the path. Although most tier 1 and 2 paths comprised very small flows and portions of the total emissions, they contributed a very large share along these directions. Controlling these paths might significantly alter the emission performance of key sectors and consequently influence the performance of the entire system.

Except for PSE_{hb}, the critical directions and paths for top powerful sectors in 2012 were different from those in 2010. The other four key sectors in top 5 in 2010 were MTP_{hb}, PSE_{tj}, PNG_{hb} and NMP_{hb}, while in 2012 they were GWP_{hb}, OMI_{hb}, PPR_{hb} and MMD_{hb}, indicating a shift in powerful sectors as well as the transform of emission structure. The major pullers (except PSE_{hb}) turned out to be more involved with basic industrial goods (e.g. gas, water, other manufactured goods and paper) within Hebei, and the primitive, upstream sectors (such as metal-related, mining- and extraction-related sectors) and sectors outside Hebei became less powerful. Powerful pulling sectors tended to be more centralized in Hebei strengthening its influence on all regions' emissions. Therefore, critical paths were often found sourcing from sectors in Hebei.

4. Discussion

Considering the economy-wide effect that any mitigation strategy entails, identifying the critical sectors and linkages of the carbon emissions transfer network will help narrow a policymaker's focus. PoP is by nature an infinite regression, encompassing both direct and indirect inter-relationships between economic sectors. The effectiveness of this method in critical sector identification has been identified in current and previous studies. Detailed comparisons of PoP with other methods have been conducted by Dietzenbacher (1992) and Luo (2013a). A direction indicates the importance of a pulling sector to a key sector. The power index of a direction is related to the complete carbon transfer between the two sectors, namely emission transfer. For example, Table 3 shows the results and rankings of these indicators for PSE_{hb}. The Spearman correlation coefficient between the two indicators for PSE_{hb} is 0.8233 ($p < 0.0001$). The difference may lie in the ideas behind the algorithms used to determine the two indicators. Directions take into account the infinite reciprocal transfers and reinforcement between the two sectors, whereas emission transfer considers only the

Table 3
The top 10 critical pulling sectors for PSE_{hb}, identified using two methods.

	Ranking	Power index	Sector	Emission transfer (Mt CO_2)	Sector
2010	1	69.146	PSE_{hb} (22)	58.606	PSE_{hb} (22)
	2	3.5425	CMD_{hb} (2)	3.2928	CMD_{hb} (2)
	3	2.9606	OTR_{hb} (27)	0.63187	SPM_{hb} (14)
	4	1.8923	TSP_{hb} (25)	0.30142	PSE_{tj} (22)
	5	0.62094	CPP_{hb} (12)	0.18041	TSP_{hb} (25)
	6	0.5143	SPM_{hb} (14)	0.13014	OTR_{hb} (27)
	7	0.4174	WRT_{hb} (26)	0.084672	NMP_{hb} (13)
	8	0.3771	MTP_{hb} (15)	0.053393	PPC_{hb} (11)
	9	0.32968	EEM_{hb} (18)	0.037183	WRT_{hb} (26)
	10	0.26561	MMD_{hb} (4)	0.023768	CPP_{hb} (12)
2012	1	76.0463	PSE_{hb}(22)	26.7789	PSE_{hb}(22)
	2	1.4869	CMD_{hb}(2)	1.0399	CMD_{hb}(2)
	3	0.4777	OTR_{hb}(27)	0.3882	SPM_{hb}(14)
	4	0.4683	OMI_{hb}(21)	0.2025	PSE_{bj}(-32)
	5	0.4207	SPM_{hb}(14)	0.1093	OTR_{hb}(27)
	6	0.3883	CPP_{hb}(12)	0.0556	NMP_{hb}(13)
	7	0.3841	EEM_{hb}(18)	0.0498	TSP_{hb}(25)
	8	0.292	MMD_{hb}(4)	0.0215	PPC_{hb}(11)
	9	0.2146	TSP_{hb}(25)	0.0078	PNG_{hb}(3)
	10	0.192	MTP_{hb}(15)	0.0076	TSP_{bj}(-29)

direct transfers. The ranking of directions indicates that some sectors deemed less important by their complete carbon transfer have a stronger power to pull the carbon emissions of key sectors (e.g., OTR_{hb} (27) in Table 3). Thus, the directions can identify important pulling sectors that might otherwise be overlooked. Dominant pullers for PSE_{hb} were similar in 2010 and 2012, since itself had largest pulling power. PSE_{hb} and CMD_{hb} in both years had pulling power larger than 1. Emission transfer showed consistent ranks (of top 4 sectors) in the two years, implying that the two sectors deserve more attention and priority when making environmental policies.

Structural paths are often ranked by the flux embodied in the path. However, flux cannot indicate the importance of the path within the entire system. In a sector with weak connectivity to other sectors, the largest share of its emissions will exit the system directly in the form of direct emissions. Even if the sector has a relatively large structural path, it will produce few indirect emissions for other sectors, which depend on the recursive high connectivity among sectors. It remains unclear to what extent controlling a structural path may affect the system's performance. Our framework provides an alternative method to determine the relative importance of paths to the key sectors in an inter-regional context. However, the ranking of the directions is derived from the power index of the same key sector. And the ranking of the directions cannot transfer directly to the corresponding structural paths. Therefore, the directions and corresponding paths of two different key sectors are not comparable. Further study will be required to determine how to rank the structural paths best in the context of the entire system.

5. Conclusion and policy implication

Some critical sectors and paths may significantly influence the performance of the entire economy (Liu et al., 2016; Othman and Jafari, 2016). In 2010, most sectors in Hebei and 11 sectors in Tianjin were identified as the key sectors pulling the carbon emissions of the entire region. In particular, energy and raw material providers were ranked as the most influential sectors in each region. Directional analysis indicated that most sectors had the greatest pulling power to themselves. Therefore, the priority in each sector should be the control of its own emissions. Cross-sector pulling typically mostly occurred within the same region. Cross-sector directions played a secondary role in pulling the carbon emissions of key sectors. Structural paths were often located in tiers 0 and 1, indicating that certain paths are rather linear and simple to focus on. Based on the analysis above, priority should be given to carbon emissions control strategies for the key sectors. Sectors in Hebei provinces require special attention due to their large effect on pulling total carbon emissions in the Jing-Jin-Ji region. Tianjin should also receive attention, for 11 of 27 sectors in Tianjin had above-average pulling power within the system in 2010, though weakened in 2012. Additionally, large indirect carbon flows along the top-ranked directions should be considered when introducing new regulations, such as green purchasing policies, for the key sectors of these directions. Determining sectors that could significantly pull the carbon emissions of multiple sectors should also be made a priority. These sectors, e.g., PSE and SPM, are mainly providers of energy and raw materials. Direct emission control is essential for developing demand-side mitigation policies for these sectors, in virtue of their large pulling powers to their own carbon emissions. Controlling the direct emissions of these sectors could significantly reduce emissions embodied along the critical directions and paths, generating a wide mitigation effect on multiple sectors. In addition, take PSE_{hb} as an example, the top pullers in the emission network reflect their pullers' high dependence on coal, because both PSE and CMD are closely related to coal combustion, which is emission-intensive. When its coal dependence was cut down, the systemic emission network would perform better with a cleaner energy structure.

By comparison with that in 2010, there were apparent changes of structure and centers in the emission network among the Jing-Jin-Ji region in 2012. Pulling power tended to concentrate in sectors in Hebei, while sectors in Beijing interacted with the other two regions more intensively in the emission network. The supply chains that link them are worth more consideration – maybe the strengthened centralization of Beijing is a challenge as well as an opportunity for carbon reduction. The cooperation may optimize the whole industrial structure in the Jing-Jin-Ji region, by engaging local advantages and more sufficient flows of products, as the integration can provide chances of resource sharing and efficiency. Encouraging green purchasing can promote cleaner production among the regions. Certain environmental standards should be promoted to actualize environmentally friendly supply chains for industries and enterprises.

PoP is a relatively new method, which requires more empirical investigation to be verified. Typically, using input-output tables of different sources (Wang, 2017; Wang et al., 2017) to validate the reliability and robustness of the PoP results might be a feasible way. However, considering that input-output tables of different sources might use different data source, varying degree of trade focus and models, further modelling on the tables, e.g. SPA, methods might show conflicting results (Moran and Wood, 2014; Owen et al., 2016; Wieland et al., 2018). Therefore, the PoP results could also vary according to the input-output data in use. In order to compare and understand the results more comprehensively, we applied our framework to the 2012 economy data of the same source for a temporal comparison, which leads to comparable but different results indicating the emission network change along with the developing economy. The PoP method is simple as well as combinative with other approaches including SPA, while its application and validation need more investigation. In general, our framework provided an indirect method to determine the relative importance of paths to the key sectors. However, further study is necessary to investigate how to evaluate the importance of the paths in the context of the entire economy.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jenvman.2018.08.018.

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